Measuring consumer switching costs in the wireless industry

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Abstract

In this paper we develop a general framework for estimating a model of consumer behavior in the wireless industry. The model reflects two distinct features of the market: durability of the handsets and potential switching costs associated with the change of service provider. In order to estimate parameters of the structural model we use consumer survey data from 2005-2009. Results using a myopic, representative consumer model suggests the presence of significant consumer switching costs associated with a change of provider amounting to approximately $230 USD. Our proposed framework allows for more complex empirical models than explored here including the introduction of persistent unobserved consumer heterogeneity in tastes for handset-carrier combinations as well as the possibility of strategic, dynamic, decision making on the part of consumers.

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Executive Summary

Consumer switching costs exist in many markets. If substantial, they may cause consumer lock-in effect that results in repeated purchases from the same supplier even when competing brands offer lower prices and better product quality. Switching costs arise when a consumer makes a seller-specific investment, which must be incurred again for a new seller. There are various sources of switching costs including investment in equipment, learning, explicit contractual obligations, etc.

Probably the most pronounced examples of consumer lock-in due to switching costs can be found in the IT industries. Incompatibility of computer operating systems, video/audio recording technologies, or telecommunication standards in the mobile phone industry makes human and physical capital investments into particular brands non-transferable when choosing alternative brands.

In this study we develop and estimate a model of consumer behavior in the wireless industry, which is characterized by nontrivial switching costs associated with the change of providers and handsets. Some components of the switching costs are potentially observable. For example, we observe average handset prices charged by carriers, while termination fees are explicitly specified in the contracts. However, a substantial part of the costs may be unobserved hassle costs of changing carriers and handsets. Using structural model of consumer behavior, we are able to recover the costs associated with changing providers, which includes unobserved hassle costs of switching. Under the assumptions of the estimated model, we estimate the switching cost to be approximately $230 USD.

Estimation results were obtained using data on extensive consumer survey of U.S. cell phone users. The data is an annual sample of 32,000 consumers from 2005-2009. It contains detailed demographic characteristics such as age, education, gender, employment status, income, etc. The dataset also contains numerous handset and carrier characteristics such as monthly subscription fee, handset price, model, type and size of display, availability and resolution of camera, etc.

In order to estimate switching costs as structural parameters we need to consider several peculiarities of the wireless industry. First, handsets are durable products and it is very unlikely that consumers who purchased new handset today will shop again in the next period. Second, difference in consumer tastes for product characteristics results in a non-trivial dynamics in the market equilibrium because carriers might rationally exploit the difference in behavior of early and late adopters of new products. Third, estimation using aggregate data requires a formal argument for the separate identification of consumer heterogeneity and switching costs. Moreover, this should be done in presence of serially correlated unobserved variables (e.g. unobserved handset and carrier characteristics). The latter statement is also related to a potential endogeneity problem if providers can choose contract arrangements, like handset price and monthly subscription fee, conditional on observing some of the variables

for which econometricians cannot control. [1]

In order to estimate structural parameters of interest we develop a general framework for modeling consumer choice in a market characterized by both product durability and switching costs. The framework admits empirical models which allow for persistent heterogeneity in consumer tastes and forward looking consumers. Potential presence of unobserved handset-carrier characteristics resulting in endogeneity problems is addressed using an instrumental variables approach. We also provide a formal argument for separate identification of consumer heterogeneity and switching costs.

Estimation results in this paper were obtained using a simple "representative consumer" model under the assumption that consumers incur switching costs only when changing service providers. That is, we assume that the purchase of a new handset with an existing carrier does not impose any costs on consumers except for monetary cost of the handset. The estimates of the switching cost parameter from this model suggest a monetary equivalent for utility costs of approximately$230. This switching cost estimate is a composite of any explicit costs involved in switching, such as incurring early termination fees if under contract, and also less tangible, implicit costs such as time on the phone with the providers setting up new service and canceling existing service, setting up billing, or the any loss of cell phone use during the switch.

It should be noted that the estimation results are the product of the simplest possible model of switching costs in a durable goods market. Although they are suggestive of significant switching costs in the wireless industry, further work is need to untangle switching costs from other possible factors. In particular, in future work we will incorporate consumer heterogeneity into the model to avoid incorrect interpretation of the "stickiness" in the observed market shares due to heterogeneity in preferences as evidence of switching costs.

[1] The issue of endogeneity is of great importance in applied economic modeling. Endogeneity exists when there is a causal loop in an economic model which does not allow for the estimated parameters to be interpreted in a causal manner. An omitted variables problem is a classic example. When a variable which is omitted from the model determines both the outcome of interest and the variables used to explain that outcome, then the estimated parameters may be biased.

1 Introduction

Consumer switching costs exist in many markets. If substantial, they may cause consumer lock-in effect that results in repeated purchases from the same supplier even when competing brands offer lower prices and better product/service quality. Switching costs arise when consumers make a seller-specific investment, which must be incurred again for a new seller. There are various sources of switching costs including investment in equipment, learning, explicit contractual obligations, etc.

Switching costs are an important issue, both theoretically and empirically. They play a central role in the analysis of market structure and industry conduct for a variety of industries, including such high technology sectors as computer software and hardware development, banking, and telecommunications. Probably the most pronounced examples of consumer lock-in due to switching costs can be found in the IT industries. Incompatibility of computer operating systems, video/audio recording technologies, or telecommunication standards in the mobile phone industry makes human and physical capital investments into particular brands non-transferable when choosing alternative brands. Some examples of other industries with consumer switching costs include banking (Sharpe (1997), Shy (2002), Kiser (2002), Kim et al. (2003)), auto insurance (Israel (2003)), airline (in relation to frequent flyer programs; Borenstein (1992)), long-distance telephone service (Knittel (1997)), and retail electricity industries (Salies (2005), Sturluson (2002)). Potential anticompetitive effects of consumer switching costs often attract attention of industry regulators.

Importance of switching costs for both business strategy and regulation is hard to overestimate. The conventional wisdom is that large switching costs affect firms' ability to raise prices for incumbent consumers above competitive level even in presence of products that are close substitutes. Rich theoretical literature on switching costs (e.g. see Farrell and Klemperer (2007) for a good review, also see Klemperer (1995)) suggest that switching costs could make markets less competitive and hence result in higher prices for consumers that are subject to lock-in effect. However, it is worth noting that under different assumptions theoretical models could make different predictions. For example, strategic behavior of consumers may result in complete dissipation of future rents earned by firms due to consumer lock-in effect through discounts offered for the first-time purchases. Interestingly, Dube et al. (2008) empirically find that consumer switching cost may have even pro-competitive effect. Therefore, both measuring consumer switching costs and evaluating its effect on competition remain important empirical questions.

Recent empirical studies document *persistence* in consumer choice data, Persistence describes a phenomena where consumers exhibit higher probability of choosing products which they have consumed in the past. When using aggregate data, this manifests itself as state dependence where the current state of the market depends on the state of the market in previous periods even after controlling for all contemporaneous product characteristics. State dependence generated by switching costs may result in unexplained "stickiness" in the distribution of market shares for products over time.

However, a pattern of stickiness in market shares can have more than one explanation. While switching costs can generate state dependence, so also can persistence in consumer preferences for product characteristics. Typically, both effects are important, which poses the challenge for empirical work. Another difficulty is related to the fact that not all relevant product characteristics are observable to the econometrician. It is quite possible that some of the unobserved characteristics could be serially correlated over time. If this is not accounted for in an empirical specification, lagged markets shares could "pick-up" this variation resulting in the incorrect interpretation of the results as evidence of state dependence. The aforementioned caveats require careful specification of the consumer choice model as well as caution when interpreting the results.

In this paper, our primary objective is to quantify consumer switching costs. To address this research question we develop a structural model of consumer choice in the wireless industry. The model has several distinct features. First, for the purpose of this study we define a "product" as a handset-carrier combination. Therefore, in order to carefully measure consumer switching costs we account for both durability of the handsets and potential utility costs associated with the change of provider and handsets. Both effects cause state dependence in consumer choices. Second, since switching costs and persistent heterogeneity in consumer preferences could generate similar pattern in observed consumer choices our framework can account for both. That being said, results presented in the paper are estimated using a "representative consumer" model. Hence, the present estimates of switching costs should be interpreted as a combination of both switching costs and unobserved heterogeneity. Third, even though we use data that contains detailed information about handset characteristics we cannot rule out possibility of demand-side unobservables. In addition to the well-known endogeneity problem, when service providers condition their policy choices (e.g. handset prices and monthly subscription fees) on the unobserved (by econometricians) variables, serial correlation in the unobservable may confound our estimates of switching costs. We address the problem by using instrumental variables approach.

2 Data

The data comes from a series of cross sectional consumer surveys collected by *comScore Inc.* from 2005 to 2009. *ComScore* administers the detailed survey to random sample of approximately 12,000 cell phone users each month to quantify market growth and cell phone usage patterns. The survey includes questions on the handset used, price paid for handset, current carrier, monthly fee for calling plan, demographic characteristics of the individual, and many other factors. In addition, *comScore* maintains a database of handset characteristics which can be matched to the cell phone model owned by an individual. Table 1 lists the relevant survey responses and handset characteristics used for this study. The sample of consumers is weighted and balanced to match national subscriber numbers and demographic characteristics.

Table 1: Variables used for estimation

Variable	Variable
Handset ID	GPS (Y/N)
Operator	Email (Y/N)
Market share (by handset-carrier)	Fullkeyboard (Y/N)
Handset price	GPRS (Y/N)
Monthly subscription fee	IM (Y/N)
Display width	MMS (Y/N)
Display height	MPEG-4 (Y/N)
Display color (65,536; B&W, etc.)	Formfactor (Candybar, Slider, etc.)
Audio type (Realtones, Monophonic, etc.)	Smartphone (Y/N)
GSM (Y/N)	OS type (Microsoft, Symbian, etc.)
CDMA (Y/N)	Camera resolution (<1mgp, 1-2mpg, etc.)

We have obtained a subset of comScore's data which reflects survey responses from the last quarter of each year starting in 2005 through 2009. The data reflect a quarterly cross section of approximately 35,000 consumers which allows us to calculate projected market shares by any combination of major carrier, handsets, and demographics on an annual basis. The major carriers include Verizon, AT&T, T-Mobile, and Sprint all of which offer virtually nationwide service.[2] All other regional or local wireless carriers are aggregated into a separate category labeled "other". Statistics on handset prices and monthly fees by carrier are shown in Table 2.

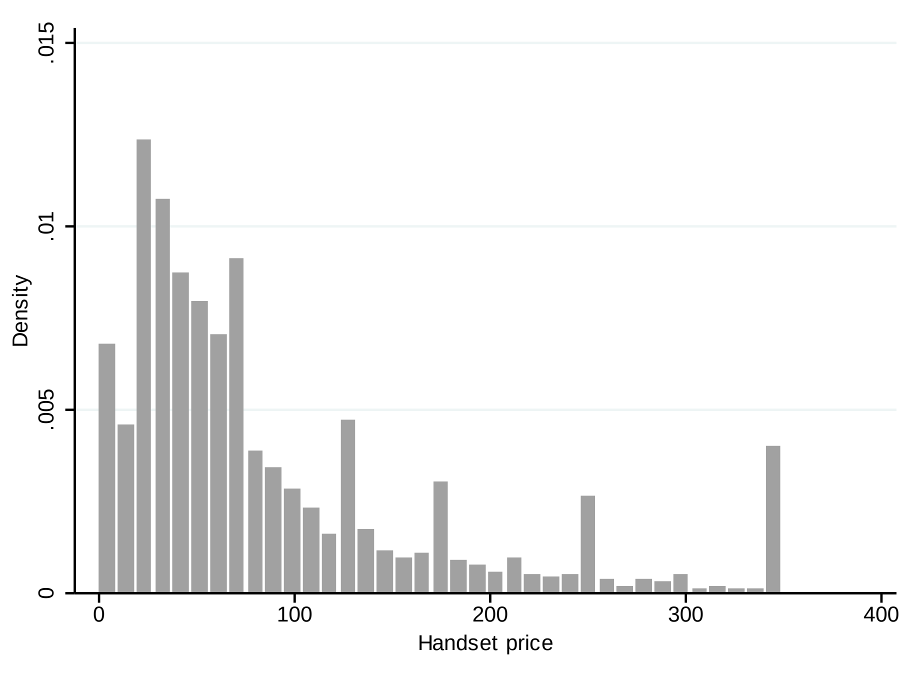
[2]There have been a few significant mergers in the industry. The largest of these was the merger of Cingular and AT&T which occurred before the beginning of our sample. A smaller, but still sizable, acquisition occurred in 2009 when Verizon acquired Alltel wireless which at the time was the fifth largest wireless company. The data provided by comScore retroactively aggregated the market shares of Alltel and Verizon together other the whole sample. Thus Verizon market shares represent the combined market shares of Alltel and Verizon customers before 2009.

Table 2: Handset prices and monthly subscription fees by carrier-year

Year	Handset price	Monthly fee	Handset price	Monthly fee	Handset price	Monthly fee
	AT&T (Cingular)		Sprint		T-Mobile	
2005	45.41	62.03	65.55	70.06	46.57	57.64
2006	57.44	64.17	77.78	68.83	59.00	58.65
2007	64.11	66.94	74.10	70.53	65.96	63.20
2008	68.29	68.37	77.50	73.94	66.33	65.81
2009	74.77	71.35	71.44	74.51	72.81	67.17
	Verizon		Other			
2005	47.83	64.09	45.87	40.62		
2006	55.49	66.37	50.75	39.81		
2007	58.48	70.84	50.81	41.44		
2008	57.87	71.56	50.76	38.19		
2009	54.03	73.32	47.75	36.83		

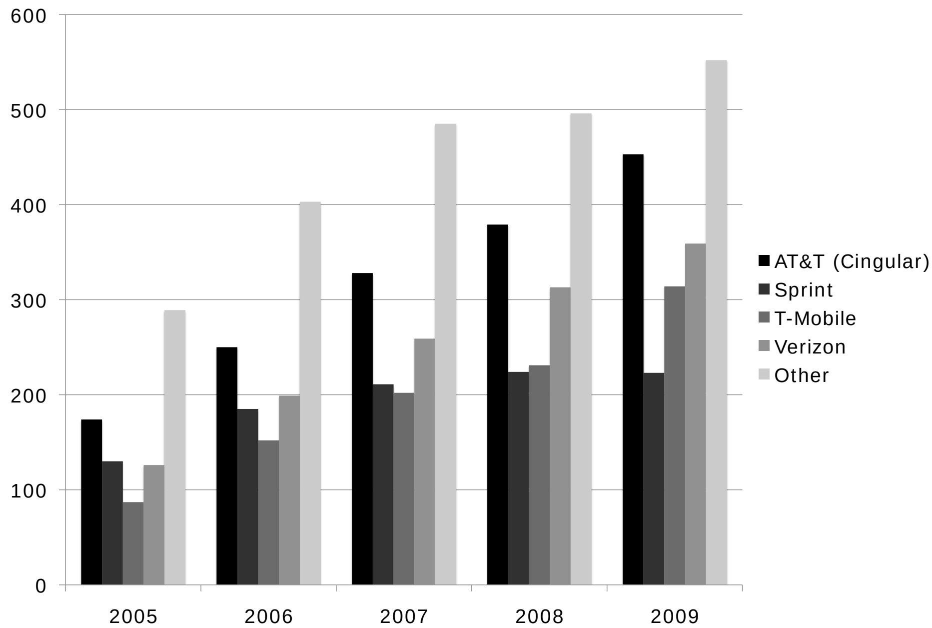
In our analysis we will be exploiting variation in the production market shares over time to identify switching costs. We define a product as a handset-carrier combination. For example, we define the iPhone on the AT&T network as a single product and calculate its market share for each year in the sample as total number of projected subscribers divided by the US population. For the price of the handset, we use the average reported handset price in that year. Histogram 1 illustrates the distribution of handset prices as reported in the survey,

Figure 1: Histogram of handset prices in the wireless industry, 2005-2009



For the carrier monthly fee, we use the average monthly fee for all subscribers to that carrier in for that year. Since handsets are durable goods, the number of possible handsets on each carrier increases overtime as new handsets are introduced by each carrier annually; when estimating the structural model we assumed that any handset available in earlier years could be used in later periods due to its durability. It is worth noting that the survey may not contain information on market shares for all possible handset-carrier combinations. Therefore, while our model will predict the entire distribution of shares, to form moment conditions we match the model predictions only to the observations available from the survey. Figure 2 summarizes number of handsets offered by different carriers in each year.

Figure 2: Number of handsets by carrier-year, 2005-2009



2.1 Evidence of state dependence

The presence of consumer switching costs imply that demand should be state dependent where distribution of market shares in the previous period will affect current period distribution of market shares. Hence, one way to check for presence of switching costs is to include lagged values of market shares into regression of the current period market shares on a set of covariates. Before proceeding with the structural model, we first provide reduced form evidence for switching costs in the wireless industry by empirically demonstrating state-dependence in the demand system.

One obvious problem with check for state-dependence is the possibility of serially correlated unobservables characteristics that affect both current and lagged market shares which would make demand appear state-dependent even in the absence of any significant switching costs. To address the problem of serially correlated unobservables we proceed as follows. Suppose we observe a set of exogenous market shares “shifters”, Z_t. Then, in a linearized reduced form model we regress current period market shares on a set of contemporaneous covariates, Z_t, and lagged market shares instrumented with the lagged covariates Z_{t-1}. Significant coefficients on the instrumented lagged shares would be consistent with the presence of state dependence.

Table 3: Evidence of state dependence in consumer choices, dependent variable s_t

VARIABLES	(1) OLS		(2) OLS		(3) IV-GMM	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
s_{t-1}	0.596***	(0.01030)	0.591***	(0.01030)	0.853***	(0.21000)
monthly fee	-3.093***	(0.38700)	0.693	(0.62700)	-0.409	(0.76800)
handset price	-0.109***	(0.01960)	-0.124***	(0.01960)	-0.5	(0.32000)
...	...	...	...	...	...	...
year dummies	No		Yes		Yes	
Constant	0.00248***	(0.00031)	0.000133	(0.00043)	0.00127*	(0.00073)
Observations	4259		4259		4259	
R-squared	0.518		0.525		0.398	

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Results of the regression are listed in table 3 and full specification results can be found in Appendix, table 6. High statistical significance of coefficients on the lagged market shares instrumented with the lagged covariates is consistent with the hypothesis of state dependent utility. In other words, it is plausible that past consumer choices have significant affect on the current period distribution of market shares.

3 Model

In this section we develop a general framework for modeling consumer choice in presence of switching costs and use a special case of the model to estimate the costs associated with switching carriers. We begin by describing the general model which allows for switching costs associated with carrier switching and handset switching as well as consumer heterogeneity and dynamic demand.

Consumers in the model are faced with period with a set of products. Let J denote a set of mobile telephony providers (carriers) and let $H_{jt},\ j \in J$ denote a set of available handsets compatible with a given carrier in period t. We assume that the number of providers does not change over time.[3] Let $\mathcal{J}_t = \{H_{jt}\}_{j \in J}$ denote consumer choice set at time t.

We assume that handsets are useless unless consumers are subscribed to one of the providers. An outside option of not having a mobile phone is included into the choice set, i.e. $o \in J,\ s.t.\ H_{ot} = \emptyset$. Each period consumers choose one of the handset-carrier combinations or an outside option.

Handsets are durable goods having observable (by econometricians) characteristics W_h that do not depreciate over time. These characteristics include attributes such as display size, availability and resolution of camera, form factor, etc. Carriers are characterized by a vector of observables X_{jt} which may change over time such as coverage quality, customer service, and monthly subscription fee. We allow for unobserved carrier and handset characteristics, summarized by a scalar ξ_{hjt}. Both consumers and providers observe ξ_{hjt} and could condition their choices upon it.

Carriers offer handsets and cellular service to a number of persistently heterogeneous consumers whose time-invariant preferences are given by *iid* draws from a distribution known up to a parameter vector. Let $a_{it} = (a_{it}^h, a_{it}^j) \in \mathcal{J}_t$ denote consumer choice of handset-carrier combination in period t. In every period a consumer type i derives utility flow from product j, which we denote as δ_{ihjt}. Let $\delta_{ihjt} = \delta_i(W_h, X_{jt}, Y_{it}, \xi_{hjt}; \theta)$ denote consumer per period flow utility from handset h and service j that depends on a set of observable carrier characteristics, X_{ijt}, observable handset characteristics, W_h, observable demographic characteristics, Y_{it}, and a scalar unobservable (by econometricians) denoted by ξ_{hjt}. It is worth noting that monthly subscription fee is treated as another (negative) dimension of service characteristics, i.e. $p_{jt} \in X_{ijt}$.

There are three types of fixed costs incurred by consumer. The first one is observable price of the handset transformed into its utility equivalent, γ_{iht}, which must be paid each time a new handset is purchased. Handsets are durable and do not depreciate. At any given point in time a consumer can have at most one handset, i.e. when new handset is purchased the old one is discarded at no cost.

The second type of fixed costs is $\psi_{iht} = \psi_{ih},\ \forall t$ representing time-invariant consumer

[3] Strictly speaking, this is not true as there are some mergers and acquisitions (e.g. Cingular purchase of AT&T in 2004) in the industry.

switching costs associated with the change of handset. It is payable whenever a new handset is purchased. This fixed cost represents hassle costs of learning new handset capabilities, like new menu, importing phone books, etc. We treat ψ_{ih} as an unobserved structural parameter to estimate.[4]

The third type of fixed costs is $\eta_{ijt} = \eta_{ij}$, $\forall t$ representing time-invariant consumer switching costs incurred when switching service provider j. It includes both hassle utility cost of the new contract underwriting as well as disutility from paying contract termination fees if incurred. We treat these costs as unobserved structural parameters to estimate.

Let $\epsilon_{it} = (\{\epsilon_{ihjt}\}_{h \in H, j \in J})$ denote a vector of choice specific iid preference draws such that

Assumption 1: *Nonpersistent consumer heterogeneity parameters ϵ_{it} are represented by iid draws from the following distribution*

$$\begin{aligned} \epsilon_{ihjt} &\overset{iid}{\sim} Extreme\ Value\ Type\ 1,\ \textit{with density} \\ f(\epsilon_{ihjt}) &= \exp(-\epsilon_{ihjt}) \exp(-\exp(-\epsilon_{ihjt})) \end{aligned}$$

Then consumer utility function conditional on the last period choice can be written as follows

$$u_i(a_{it}, a_{it-1}, \cdot) = \begin{cases} -\eta_{ij} - \psi_{ih} - \gamma_{iht} + \delta_{ihjt} + \epsilon_{ihjt}, & \text{if } a^h_{it} \neq a^h_{it-1}, a^j_{it} \neq a^j_{it-1} \\ -\psi_{ih} - \gamma_{iht} + \delta_{ihjt} + \epsilon_{ihjt}, & \text{if } a^h_{it} \neq a^h_{it-1}, a^j_{it} = a^j_{it-1} \\ -\eta_{ij} + \delta_{ihjt} + \epsilon_{ihjt}, & \text{if } a^h_{it} = a^h_{it-1}, a^j_{it} \neq a^j_{it-1} \\ \delta_{ihjt} + \epsilon_{ihjt}, & \text{otherwise} \end{cases} \tag{1}$$

In other words, in every period consumer can choose to change handset, change provider, change both, or stay with the same choice as in the previous period. We normalize utility from outside option to zero, i.e. $\delta_{ih0t} = 0\ \forall i, t, h$.

3.1 Myopic consumers

Durability and potential switching costs call for strategic decisions by consumers. In particular, consumers may choose to delay purchase and wait until the product/service becomes more affordable. In presence of significant switching costs, a consumer may choose to keep current subscription even when current utility flow rationalizes disconnection. This would happen if expected discounted value of future utility flows seems bright enough.

[4] In the empirical model used to estimate the results in this version of the paper, ψ_{ih} is fixed to be zero.

On the other hand, it is not obvious if there are significant benefits to strategic behavior in the market for wireless industry. Predicting future product offerings of carriers may be difficult for consumers to do. In addition, a dynamic model of consumer behavior significantly complicates estimation procedure because for any given parameter vector we would need to numerically solve a complex dynamic programming problem. For these reasons, in this version of the paper we assume that consumers are not patient. That is, we assume that their decisions do not take into account expectations over the future realizations of payoff relevant variables. In the forthcoming versions of the paper we will develop an alternative dynamic model of consumer behavior. Rather they are myopic, in that their choices are based on the current period utility only. For the interested reader we have provided the framework for the fully rational dynamic model in the appendix of this paper.

Assumption 2: *Consumers' choices are non-strategic, i.e. whenever choosing between available options consumers take into account only current period utility.*

In every period, consumer utility function depends on the choice made in the previous period. In particular, probability of making choice a_{it} is given by

$$\begin{aligned}
\Pr(a_{it}|a_{it-1}) &= \Pr(u(a_{it}, a_{it-1}, \cdot) \geq u(\tilde{a}_{it}, a_{it-1}, \cdot),\ \forall \tilde{a}_{it} \in \mathcal{J}_t) \\
&= \int \cdots \int \mathbb{1}\left[u(a_{it}, a_{it-1}, \cdot) \geq u(\tilde{a}_{it}, a_{it-1}, \cdot),\ \forall \tilde{a}_{it} \in \mathcal{J}_t)\right] dF_\epsilon(\cdot) \\
&= \frac{\exp(u(a_{it}, a_{it-1}, \cdot))}{\sum_{\tilde{a}_{it} \in \mathcal{J}} \exp(u(\tilde{a}_{it}, a_{it-1}, \cdot))},
\end{aligned}$$

where the last line is due to the Assumption 1.

Let s_{iat} denote a share of consumer type i choosing handset-carrier combination $a_{it} \in \mathcal{J}_t$ in period t. Then in any $t > 0$ current share of consumer type i choosing alternative a_{it} is defined by

$$s_{iat} = \sum_{\tilde{a}_{it-1} \in \mathcal{J}_{t-1}} s_{i\tilde{a}t-1} \cdot \Pr(a_{it}|\tilde{a}_{it-1}). \tag{2}$$

Note that outside option is a part of any $\mathcal{J}_{t-1}$.

The model nests two special cases in the recent IO literature. First, if there are no switching costs for handsets and carriers and disutility from price of the handset, γ_{iht}, is observed, the model becomes a standard durable good model where consumer choice of the currently available products depends on the current holdings. Second, if there are no switching costs the product price must be paid every period, i.e. it is not durable, the model becomes standard random utility BLP model.

3.2 Aggregate demand schedule

In the previous sections we defined market share for each of the consumer types. In order to obtain aggregate market shares we need to integrate over the distribution of consumer types.

Assumption 3: *Persistent heterogeneity in consumer preferences is represented by random coefficients that are drawn from a distribution, known up to a parameter vector, i.e. let α_i denote a vector of marginal utilities from product characteristics for consumer type i. Then*

$$\alpha_i \overset{iid}{\sim} F_\alpha(\cdot|\theta)$$

Let $G_\delta(\cdot|\theta)$ denote joint distribution of per-period consumer flow utilities implied by assumption (3) conditional on observable product characteristics and for given values of the demand-side unobservable ξ_{hjt}. Then aggregate market shares can be obtained as follows

$$s_{hjt} = \int \cdots \int s_{ihjt}(\{\delta_{ikt}\}_{k\in\mathcal{J}_t}, \{s_{ikt-1}\}_{k\in\mathcal{J}_{t-1}}; \theta) dG_\delta(\cdot|\theta) \tag{3}$$

where the initial distribution of consumer types across market shares, $\{s_{ik0}\}_{k\in\mathcal{J}_0}$ is given.[5] To simulate aggregate market shares we can use a simple frequency simulator.[6]

Let $\bar{\delta}_{hjt}$ denote mean population flow utility from handset-carrier combination (h, j). Then individual flow utilities for each consumer type i can be obtained as follows

$$\delta_{ihjt} = \bar{\delta}_{hjt} + \tilde{\delta}_{ihjt},$$

where $\tilde{\delta}_{ihjt}$ stands for consumer i's utility deviations from the mean population utility. This decomposition of flow utility is useful for estimation purposes. In particular, for any given parameter vector, including parameters of the distribution of consumer heterogeneity, we can invert out $\bar{\delta}_{hjt}$ by matching model predictions to the observed market shares at handset-carrier level, that is, we can find such sequence of $\{\bar{\delta}_{hjt}\}_{t=0,\dots,T;hj\in\mathcal{J}_t}$ that satisfy the following equation

$$s_{hjt} = \hat{s}_{hjt}(\{\bar{\delta}_{hjt}\}_{t=0,\dots,T;hj\in\mathcal{J}_t}, \cdot|\theta) \tag{4}$$

An important issue here is uniqueness of the sequence $\{\bar{\delta}_{hjt}\}_{t=0,\dots,T;hj\in\mathcal{J}_t}$ that rationalizes observed market shares. Berry (1994) establishes uniqueness argument for a static random

[5] For a representative consumer version of the model we do not have "initial conditions problem" and can use observed market shares at the beginning of the sample period. For random coefficients model we would need to simulate the initial conditions.

[6] In many cases, there are alternative simulation techniques (e.g. importance sampling) which might have better statistical properties.

coefficients model in case where products are substitutes. It is conceivable that the same argument could be used for a myopic consumers model in our setup. In practice, when implementing our estimation procedure, we end up using different starting values for the sequence to be inverted and have found that they all converge to the same set of numbers.

3.3 Special case: a representative consumer model

In the simplest version of our model we assume that consumers do not have persistent heterogeneity in tastes. All differences in consumer types boil down to a current period vector of iid preference draws from a distribution known up to a parameter vector (assumption 1). It is worth noting that the results of the simple version of the model should be interpreted carefully to the extent that persistence in consumer tastes for product characteristics could generate "stickiness" of aggregate market shares, which, in turn, could be erroneously attributed to switching costs.

Differently from the random coefficients model our simple specification allows us to abstract away from the initial conditions problem by using observed initial period market shares. Therefore, when estimating a representative consumer version of the model we assume that $s_{ihjt} = s_{hjt}$, $\forall i$, except for the iid draws from extreme values distribution.

4 Empirical specification and estimation

In this section we outline functional form assumptions on the per period consumer flow utility. At this stage, we choose a simple linear specification for $\delta_i(W_h, X_{jt}, Y_{it}, \xi_{hjt}; \theta)$. In addition, we make several restrictions on consumer heterogeneity and rationality. First, we assume that there are no persistent consumer heterogeneity and all differences in consumer choices are due to the current period idiosyncratic preference draws ϵ_{it}. Second, we assume that there are no switching costs associated with the change of the handset aside from the price that consumers must pay for the new handset. This assumptions rules out hassle costs associated with learning to use a new handset while retaining the same carrier. Third, we assume that consumers are making myopic decisions when choosing current period handset-carrier combination. These three assumptions will be relaxed in the next versions of the paper. Finally, we impose the following functional form restrictions on the flow utility.

Assumption 4: *Suppose that per period consumer utility function satisfy the following functional restriction,*

$$\delta(W_h, X_{jt}, Y_{it}, \xi_{hjt}; \theta) = \alpha_0 + \alpha^p p_{jt} + \beta W_h + \xi_{hjt},$$

where the only carrier-specific observable is monthly fee, i.e. $X_{jt} = p_{jt}$.

Note that we do not condition on the demographic variables, which is due to the "representative consumer" assumption. Also, since γ_{iht} is observable and expressed in dollars, we require it to have the same disutility from price as α^p in the flow utility specification.

Assumption 5: *All consumers face the same switching cost associated with the change of provider and no switching costs associated with the change of handset, i.e.*

$$\psi_{ih} = 0, \ \forall i, h$$
$$\eta_{ij} = \eta, \ \forall i, j$$

To recapitulate, in this version of the paper we estimate a representative consumer model assuming myopic consumer choices and zero switching costs associated with the change of the handset. We allow for non-persistent consumer heterogeneity, durability of the handsets, and switching costs associated with the change of carrier.

To estimate the model we start with observed distribution of market shares in 2005. Given that, we calculate model predictions using myopic consumer model for each of the consecutive periods. Note that as time progress we allow consumers to keep their initially purchased handset throughout the entire history. Thus, our structural model generates a matrix of consumer holdings for each handset-carrier combination ever observed in the market. Since the survey data may not cover all possible handset-carrier combinations, to invert out mean flow utilities we used only those predictions that correspond to the observed shares in the data. Given a linear per-period utility specification, conditional on observables and for any trial parameter values we can isolate sequence of unobservables $\xi_{hjt}, \ \forall h, j, t$ and form moment conditions based on

$$g_i(\theta) = E[\xi_{hjt} \otimes \mathbf{Z}] = 0, \tag{5}$$

where $\mathbf{Z}$ is a set of instruments discussed in the section that follows.

To obtain parameter estimates we used two-stage efficient GMM procedure. In the first stage, weighting matrix is chosen to be $(\mathbf{Z}'\mathbf{Z})^{-1}$, which would be optimal for a linear model. In the second stage, we computed optimal weighting matrix using our estimates from the first stage.

5 Instruments and identification

In this section we provide an argument for identification of consumer switching costs in presence of serially correlated unobservable. Note that since we estimate a representative consumer version of the model we do not discuss separate identification of consumer heterogeneity and switching costs formally. This discussion is left for further research.[7]

Let's focus on identification of consumer switching costs in case of representative consumer specification. First, suppose that the data was generated by the representative consumer model. Then, in absence of switching costs the evolution of aggregate market shares should be rationalizable with a myopic consumers durable goods model. Note that since handset prices are observable they do not confound identification of switching costs. If there are significant consumer switching costs payable upon changing service provider, dynamic evolution of market shares should uniquely pin down additional parameters of interest. Namely, increase in the switching costs would result in a different consumers dynamic "arrival pattern". Higher switching costs would result in greater proportion of consumers coming from the outside option than from the rival providers. This also has an implication that larger cumulative share of rival providers would be associated with smaller increase in own market shares for the same increase in observable product characteristics and vice versa.

Note that differently from a typical durable good model, in our model we have additional parameters that have to be identified using additional moment restrictions. Since switching costs are essentially coefficients on the last period consumer choices, moment conditions based on the last period exogenous shifters should be informative in identifying consumer switching costs in our model.

Formally, our identification relies on moment conditions defined as follows:

$$E[\xi_{hjt}|Z_{hjt}, Z_{hjt-1}] = 0, \tag{6}$$

where Z_{hjt} stands for current period exogenous variables. Following existing literature we assume that Z_{hjt} consists of own product characteristics (except for handset price and monthly subscription fees) and a set of instrumental variables used in Berry et al. (1995). Namely, in addition to own product characteristics we included average characteristics of handsets offered by rival service providers in any given period. The rationale behind our instruments is similar to one used in earlier literature. In particular, we assume that proximity in the characteristics space between different alternatives affects price-cost markups through substitutability of the products. As long as observed characteristics of the competing products

[7] At this point, we can only outline the logic behind the formal identification proof for heterogeneity and switching costs, which is forthcoming in the next versions of the paper. The idea relies on recent study by Berry and Haile (2009) who formally prove non-parametric identification of random coefficients model using aggregate data. In case of state dependent utility we can extend their argument by claiming that identification of consumer heterogeneity comes from cross-sectional variation in the data. Then for any given distribution of consumer types, identification of switching costs comes from time-series variation in the data.

are predetermined (i.e. uncorrelated with the unobservables) we could construct a set of valid instruments that are correlated with handset price and monthly fees. Note that this assumption and moment conditions defined in equation (6) address the problem of endogeneity of handset price and monthly subscription fee. Indeed, if mobile telephony service providers observe ξ_{hjt} prior to making their policy choices, they would condition prices they charge on the realizations of the unobservable. If own (and rivals') product characteristics are determined exogenously than orthogonality conditions implied by the equation (6) would hold. Extra moments based on the lagged values of covariates, Z_{hjt-1}, should be informative about the size of consumer switching costs.

6 Estimation results: Representative Consumer Model

We begin our analysis by estimating several specifications for a "misspecified" static logit model of consumer behavior in the wireless industry as a comparison point. Static specifications are similar to Berry (1994) and allow for product-service specific scalar unobservable. In this study, we attach conventional interpretation to the unobservable, i.e. it stands for unobserved (by econometricians) product-service characteristics. Coverage quality and customer service might be examples of the factors that we cannot control for. As discussed above, we use instrumental variable approach to solve the problem.

Results of the static logit model specifications are listed in Table 4. Complete table of the coefficient estimates can be found in Appendix, table 7.

Table 4: Estimation results, logit model, OLS and IV

VARIABLES	(1) OLS		(2) OLS		(3) IV-GMM	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
price	-0.00531***	(0.00035)	-0.00588***	(0.00035)	-0.00687**	(0.00327)
...	...	...	...	...	...	
year dummies	No		Yes		Yes	
Constant	-8.133***	(0.23500)	-7.349***	(0.24100)	-7.574***	(0.71500)
Observations	4769		4769		4259	
R-squared	0.237		0.263		0.273	

Standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Note that using instrumental variable increases absolute value of the coefficient on the variable "price", which is a sum of handset price (appropriately normalized to monthly level) and monthly subscription fees. This result is expected given that price and unobserved product characteristics are likely to be positively correlated. In other words, using instrumental variables has the expected effect on the coefficient on price, which is consistent with the hypothesis of endogeneity of handset price and monthly subscription fees.

One undesirable feature of the simple logit specification is that it implicitly assumes that all consumers who purchased a handset and signed a contract in the current period must do the same thing next period. Durability of the handsets and long-lasting subscriber contracts, which are subject to severe termination fees, make static model highly unrealistic.

In order to properly address these issues we estimate a simple model of consumer behavior with switching costs as outlined previously. Recall that we assumed away any persistent heterogeneity in consumer tastes. In particular, price sensitivity and marginal utility from product characteristics are assumed to be the same for all consumers in the market. The only distinction between different consumer types arises due to *iid* (across consumers and time periods) idiosyncratic preference draws. Also, even though consumers face switching costs and have to pay handset price any time they switch service provider, we rule out any dynamic,strategic behavior.

When estimating parameters of the switching cost model we account for both endogeneity of prices and the fact that we have to estimate extra parameter. Endogeneity is addressed in a way similar to the static model, that is, we used BLP-type instrumentsBerry et al. (1995). Additional structural parameters are estimated using extra moment conditions that are based on the orthogonality conditions of lagged market shares "shifters" and current period unobservables.

Estimation results for the structural model are presented in table 5 (full specification results can be found in Appendix, table 8).

Table 5: Preliminary estimation results for the structural model

Variables	1^{st}-stage GMM		2^{nd}-stage GMM	
	coef.	s.e	coef.	s.e.
sw. costs (utility)	0.68862	(0.31602)	0.84444	(0.30432)
sw.costs (USD)	225.70		236.30	
const.	-5.89870	(0.55750)	-5.53900	(0.56037)
monthly fee	-0.03661	(0.00773)	-0.04288	(0.00782)
...	...	...	...	...

The estimates from a representative consumer model of switching costs suggest a monetary equivalent of utility costs in a range from $225.70 to $236.30 for switching from one carrier to another. To put this in perspective, one can compare the estimate to observable switching costs. For example, contracts with most carriers require an early termination fee to be paid if the consumers switches carriers while still under contract. Currently, early termination fees (ETFs) range from $175 to $200 for most carriers, although smart phone termination fees have recently been pushed higher on some carriers. Comparing the estimates of switching costs to ETFs at a level of $175 would suggest that there are additional hassle costs of around $50 associated with switching. This comparison would be appropriate if every consumer paid ETFs whenever they switched carriers. In reality, some proportion of cell phone users face zero termination fees when considering switching because their contracts have expired. Thus, the average ETF paid by switching consumers is most certainly less than the ETFs observed in contracts. This implies that that $50 would be a lower bound on the unobserved hassle costs of switching. If the special case of the model we estimated is correct then additional unobserved hassle costs would be in a range of about $50 to $230.

7 Discussion

We developed a structural model of consumer choice in the wireless industry. In the model consumers choose between various handset-carrier combinations taking into account both durability of the handsets and switching costs associated with the change of the mobile telephony service providers as well as costs of learning new hardware. The model allows for demand-side unobservables in the spirit of Berry et al. (1995) and related endogeneity problem when carriers can condition handset price and monthly subscription fee on the realized values of the unobservables. We allow for persistent heterogeneity in consumer tastes by using random coefficients specficiation.

In order to evaluate consumer switching costs in the wireless industry we proceed in two steps. First, we test for potential state dependence using linearized version of the model where current period market shares are regressed on a set of contemporaneous exogenous market shares' shifters and own lagged values instrumented with the lagged values of exgoneous regressors. This specification accounts for potential endogeneity of handset price and market shares as well as for serially correlated unobservables. Estimation results are consistent with significant state dependence in consumer choices. Also, we estimated a "misspecified" static model of consumer choice where the product becomes obsolete by the end of each period. By comparing OLS specification and instrumental variable approach, we find that the change in coefficients is consistent with at least some degree of endogeneity of handset price and monthly subscription fee.

Second, we estimated a special case of the general model, namely its representative consumer version. In particular, in the empirical specification we assumed away any persistence in consumer tastes and allow for non-persistent consumer heterogeneity represented by iid (over consumers, products, and time periods) preference draws from a distribution known up to a parameter vector. Our empirical specification imposes significant restrictions on the structural model developed. In particular, the estimates of the switching costs should be treated with caution as they are likely to represent both consumer switching costs and persistence in consumer preferences. We assume away any learning or hassle costs associated with purchasing a new device on the same carrier.

The results of the simple empirical specification suggest that consumers face significant switching costs amounting to about \$236 whenever they choose to switch their service providers. Confidence intervals are fairly tight as both first and second stage GMM results suggest that the switching costs coefficients are significant at 1% level.

That being said, one should be careful when interpreting the results. First, since the representative consumer model does not account for persistent heterogeneity in consumer preferences, parameter estimates are likely to lump both together. Second, the assumptions of negligible hassle costs associated with purchasing a new device on the same carrier and nonstrategic (myopic) consumer behavior may not be reasonable, though their importance for the final results is not clear. These caveats will be carefully investigated and addressed in the later refinements of this paper.

A Extension to forward-looking consumers

In this section we discuss a possible extension of the model that allows consumers to make dynamic decisions. As we note in the subsection above, long-term nature of relationship between consumers and providers is likely to arise due to handsets durability and potential switching costs associated with the change of provider and handset.

One way to incorporate strategic decision making into the model of consumer behavior is to follow model proposed in Melnikov (2001) and its extension to multiple consumer types in Gowrisankaran and Rysman (2007). In these models, consumers have boundedly rational beliefs about the evolution of payoff-relevant state variables.

In particular, let Ω_t denote current handset-carrier attributes and any other factors that influence future product attributes. Assume, that Ω_t evolves as a first-order Markov process, i.e. $P(\Omega_{t+1}|\Omega_t, \mathcal{I}_t) = P(\Omega_{t+1}|\Omega_t)$, where $\mathcal{I}_t$ denotes full information set at time t (including entire history of the market). Then state variables vector for consumer type i is $(\epsilon_{it}, \delta^0_{ihjt}, \Omega_t)$, where δ^0_{ihjt} is the flow utility from the currently held handset-carrier combination. Note that total utility from current holding is given by $u_{i0t} = \delta^0_{ihjt} + \epsilon_{ihjt}$. Therefore, we can define the Bellman equation for consumer type i as follows

$$V_i(\epsilon_{it}, \delta^0_{ihjt}, \Omega_t) = \max \left\{ \begin{array}{l} u_{i0t} + \beta E\left[EV_i(\delta^0_{ihjt}, \Omega_{t+1}|\Omega_t\right], \\ \max\limits_{j,h} \left\{u_{ihjt} + \beta E\left[EV_i(\delta_{ihjt}, \Omega_{t+1})|\Omega_t\right]\right\} \end{array} \right\}, \tag{7}$$

where u_{ihjt} is defined as in (1) and

$$EV_i(\delta^0_{ihjt}, \Omega_t) = \int \cdots \int V_i(\epsilon_{it}, \delta^0_{ihjt}, \Omega_t) dF_\epsilon.$$

Note that for an individual that has purchased a product in the past, $\delta^0_{ihjt} = \delta^0_{i\hat{h}\hat{j}\hat{t}}$, where $\hat{t}$ is the most recent period of purchase, and $(\hat{h}, \hat{j})$ are the identities of handset and carrier chosen.

Obviously, large dimensionality of Ω_t makes it very difficult to numerically solve for value functions. Therefore, we proceed similar to earlier literature by making assumption about consumer beliefs. In particular, for each handset-carrier combination we define

$$\Delta_{ihjt}(\Omega_t) = \delta_{ihjt} - \psi_{ih}\mathbb{1}(a^h_{it} = a^h_{it-1}) - \eta_{ij}\mathbb{1}(a^j_{it} = a^j_{it-1}) - \gamma_{iht} + \beta E\left[EV_i(\delta^0_{ihjt}, \Omega_{t+1}|\Omega_t\right] \tag{8}$$

being the expected discounted utility for consumer i purchasing product (h, j) at time t, integrated over ϵ_{it} vector. Also, let

$$\delta_{it}(\Omega_t) = \ln\left(\sum_{k\in\mathcal{J}_t} \exp(\Delta_{ihjt}(\Omega_t))\right) \tag{9}$$

denote the logit inclusive value for consumer i at time t. Note that specific properties of the extreme value type 1 errors imply that the logit inclusive values is a sufficient statistic for the state of the entire market.

Finally, similar to Gowrisankaran and Rysman (2007), we make the following assumption

Assumption 6: *Inclusive value sufficiency*

$$P(\delta_{it+1}|\Omega_t) = P(\delta_{it+1}|\Omega'_t) \textit{ if } \delta_{it}(\Omega_t) = \delta_{it}(\Omega'_t).$$

Assumption 6 is often referred to as "bounded rationality" of consumer beliefs. This is because according to this assumption consumers predict future evolution of market using information contained in the logit inclusive values statistic only.

Despite the fact that assumption 6 is very restrictive it allows for a feasible solution to the consumer dynamic programming problem because state space of the problem is now reduced to a pair $(\delta^0_{ihjt}, \delta_{it})$ (after integrating out ϵ_{it}). Note that the expectation Bellman equation can now be written as

$$EV_i(\delta^0_{ihjt}, \delta_{it}) = \ln\left[\exp(\delta_{it}) + \exp\left(\delta^0_{ihjt} + \beta E\left[EV_i(\delta^0_{ihjt}, \delta_{it+1})\right]\right)\right] + 0.5772$$

Aggregate consumer policy functions (individual consumers' shares) can be obtained as the probability of purchase times the probability of purchasing a given product conditional on purchase, i.e.

$$\begin{aligned}\hat{s}_{ihjt}(\delta^0_{ihjt}, \Delta_{ihjt}, \delta_{it}) &= \frac{\exp(\delta_{it})}{\exp(\delta_{it}) + \exp(\delta^0_{ihjt} + \beta E[EV_i(\delta^0_{ihjt}, \delta_{it+1})|\delta_{it}])} \times \frac{\exp(\Delta_{ihjt})}{\exp(\delta_{it})} \\ &= \exp(\Delta_{ihjt} - EV_i(\delta^0_{ihjt}, \delta_{it})) \qquad (10)\end{aligned}$$

B Estimation Tables

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Table 6: Evidence of state dependence, dependent variable s_t

VARIABLES	(1) OLS		(2) OLS		(3) IV-GMM	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
s_{t-1}	0.596***	(0.01030)	0.591***	(0.01030)	0.853***	(0.21000)
monthly fee	-3.093***	(0.38700)	0.693	(0.62700)	-0.409	(0.76800)
handset price	-0.109***	(0.01960)	-0.124***	(0.01960)	-0.5	(0.32000)
dispsize	0.000148***	(0.00005)	0.000150***	(0.00005)	0.000271***	(0.00009)
polyreal	0.00002	(0.00006)	3.60E-05	(0.00005)	9.87E-06	(0.00007)
gsm	-0.00005	(0.00007)	6.02E-05	(0.00007)	7.23E-06	(0.00010)
cdma	0.00005	(0.00004)	8.74E-06	(0.00004)	-5.57E-06	(0.00010)
b&w display	-0.00006	(0.00006)	-6.18E-05	(0.00006)	-7.98E-05	(0.00007)
gps	8.30e-05**	(0.00004)	6.00E-05	(0.00004)	1.79E-05	(0.00005)
email	0.00000	(0.00003)	-2.22E-06	(0.00003)	8.41e-05*	(0.00004)
fullkeyboard	0.000330***	(0.00005)	0.000354***	(0.00005)	0.000311***	(0.00005)
gprs	-0.00010	(0.00007)	-7.33E-05	(0.00007)	-8.82E-05	(0.00009)
im	-0.00004	(0.00003)	-4.09E-05	(0.00003)	-5.30E-05	(0.00004)
mms	9.92e-05***	(0.00003)	0.000100***	(0.00003)	5.44E-05	(0.00007)
mpeg4	0.000115***	(0.00003)	0.000111***	(0.00003)	0.000122*	(0.00007)
form1	0.00000	(0.00008)	-1.63E-05	(0.00008)	-7.73E-05	(0.00009)
form2	0.00012	(0.00008)	0.000106	(0.00008)	-5.98E-05	(0.00011)
form3	0.00005	(0.00010)	2.17E-05	(0.00010)	0.000135	(0.00019)
form4	0.00002	(0.00009)	1.29E-05	(0.00009)	-1.52E-05	(0.00011)
form5	-0.00017	(0.00010)	-0.000194*	(0.00010)	-0.000134	(0.00012)
smartphone	-0.00030	(0.00020)	-0.000256	(0.00020)	-9.87E-05	(0.00024)
os1	0.00156***	(0.00025)	0.00156***	(0.00025)	0.00161***	(0.00049)
os2	-0.00009	(0.00014)	1.16E-06	(0.00014)	0.00035	(0.00043)
os3	-0.00010	(0.00020)	-0.000166	(0.00020)	-6.33E-05	(0.00022)
os4	0.00002	(0.00021)	-4.73E-05	(0.00021)	-1.16E-05	(0.00024)
os5	0.00013	(0.00020)	7.81E-05	(0.00020)	6.72E-05	(0.00023)
os6	0.00004	(0.00020)	-7.47E-06	(0.00020)	0.00023	(0.00027)
cam.res1	-0.000289***	(0.00008)	-0.000351***	(0.00008)	-0.000654***	(0.00018)
cam.res2	-0.000148**	(0.00008)	-0.000192**	(0.00007)	-0.000427***	(0.00016)
cam.res3	-0.00009	(0.00007)	-0.000121*	(0.00007)	-0.000268**	(0.00013)
year dummies	No		Yes		Yes	
Constant	0.00248***	(0.00031)	0.000133	(0.00043)	0.00127*	(0.00073)
Observations	4259		4259		4259	
R-squared	0.518		0.525		0.398	

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 7: Logit regression, dependent variable $\ln(s_t) - \ln(s_0)$

VARIABLES	(1) OLS		(2) OLS		(3) IV-GMM	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
price	-0.00531***	(0.00035)	-0.00588***	(0.00035)	-0.00687**	(0.00327)
dispsize	0.325***	(0.08430)	0.376***	(0.08300)	0.408***	(0.11800)
polyreal	0.494***	(0.09310)	0.517***	(0.09160)	0.525***	(0.10000)
gsm	-0.230**	(0.11500)	-0.196*	(0.11400)	-0.138	(0.13400)
cdma	-0.219***	(0.07500)	-0.219***	(0.07380)	-0.191**	(0.09600)
b&w display	-0.065	(0.09700)	-0.108	(0.09550)	-0.161	(0.10500)
gps	0.315***	(0.06490)	0.340***	(0.06380)	0.317***	(0.06650)
email	-0.199***	(0.05670)	-0.185***	(0.05580)	-0.147**	(0.06960)
fullkeyboard	0.596***	(0.08600)	0.678***	(0.08490)	0.659***	(0.08860)
gprs	-0.237**	(0.11300)	-0.239**	(0.11100)	-0.297**	(0.12300)
im	0.182***	(0.05070)	0.176***	(0.04980)	0.155***	(0.05280)
mms	0.309***	(0.05930)	0.307***	(0.05830)	0.312***	(0.06200)
mpeg4	0.135**	(0.05520)	0.134**	(0.05430)	0.172***	(0.06590)
form1	0.17	(0.15000)	0.0636	(0.14800)	0.045	(0.14900)
form2	0.743***	(0.14800)	0.652***	(0.14600)	0.627***	(0.15200)
form3	0.295	(0.18100)	0.164	(0.17800)	0.295	(0.22000)
form4	0.501***	(0.16200)	0.430***	(0.16000)	0.418***	(0.15900)
form5	-0.362*	(0.18700)	-0.533***	(0.18500)	-0.577***	(0.19200)
smartphone	-0.143	(0.36900)	-0.135	(0.36300)	-0.0996	(0.37500)
os1	2.270***	(0.45900)	2.340***	(0.45200)	2.401***	(0.50900)
os2	0.781***	(0.25700)	0.816***	(0.25300)	0.957**	(0.44600)
os3	-0.627*	(0.37100)	-0.664*	(0.36500)	-0.657*	(0.36400)
os4	-0.0648	(0.39200)	-0.0911	(0.38600)	-0.117	(0.38600)
os5	-0.00468	(0.37900)	-0.0184	(0.37300)	0.0316	(0.36900)
os6	-0.551	(0.37600)	-0.6	(0.37000)	-0.61	(0.40400)
cam.res1	0.12	(0.14200)	-0.124	(0.14200)	-0.19	(0.24500)
cam.res2	0.359***	(0.13900)	0.188	(0.13800)	0.168	(0.21200)
cam.res3	0.308**	(0.13700)	0.21	(0.13500)	0.173	(0.17500)
year dummies	No		Yes		Yes	
Constant	-8.133***	(0.23500)	-7.349***	(0.24100)	-7.574***	(0.71500)
Observations	4769		4769		4259	
R-squared	0.237		0.263		0.273	

Standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

Table 8: Results of the structural model

Variables	1^{st}-stage GMM		2^{nd}-stage GMM	
	coef.	s.e	coef.	s.e.
sw. costs (utility)	0.68862	(0.31602)	0.84444	(0.30432)
sw.costs (USD)	225.70		236.30	
const.	-5.89870	(0.55750)	-5.53900	(0.56037)
monthly fee	-0.03661	(0.00773)	-0.04288	(0.00782)
dispsize	0.37524	(0.07043)	0.35478	(0.07010)
polyreal	0.52299	(0.08903)	0.53908	(0.08932)
gsm	-0.28380	(0.11746)	-0.21357	(0.11760)
cdma	-0.21704	(0.07528)	-0.14925	(0.07543)
b&w display	-0.06992	(0.09675)	-0.07900	(0.09686)
gps	0.35551	(0.06104)	0.36762	(0.06117)
email	-0.19433	(0.05732)	-0.17882	(0.05734)
fullkeyboard	0.63955	(0.08234)	0.65215	(0.08229)
gprs	-0.26351	(0.11589)	-0.32341	(0.11608)
im	0.19123	(0.05169)	0.19253	(0.05166)
mms	0.29034	(0.05908)	0.29756	(0.05905)
mpeg4	0.13916	(0.05592)	0.11822	(0.05589)
form1	0.13353	(0.13744)	0.14467	(0.13709)
form2	0.71012	(0.13525)	0.72278	(0.13489)
form3	0.24300	(0.16348)	0.22636	(0.16343)
form4	0.48359	(0.14861)	0.47435	(0.14824)
form5	-0.44555	(0.16500)	-0.45820	(0.16450)
smartphone	-0.16976	(0.36483)	-0.17072	(0.36343)
os1	2.35040	(0.50943)	2.38270	(0.50877)
os2	0.79631	(0.21019)	0.77007	(0.20960)
os3	-0.62172	(0.36393)	-0.62465	(0.36270)
os4	-0.08360	(0.38338)	-0.03462	(0.38244)
os5	0.00242	(0.37362)	0.01194	(0.37240)
os6	-0.54968	(0.36402)	-0.53828	(0.36272)
cam.res1	-0.03577	(0.13561)	-0.05435	(0.13503)
cam.res2	0.25710	(0.13413)	0.23775	(0.13363)
cam.res3	0.25930	(0.13322)	0.23389	(0.13275)